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THE ROLE OF SOCIAL FACTORS IN THE ACCEPTANCE OF ARTIFICIAL INTELLIGENCE-BASED SERVICES: THE EXAMPLE OF THE BANKING SECTOR OF BOSNIA AND HERZEGOVINA

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Abstract

In times when AI's development and research is moving at an unprecedented speed, this paper explores its role in retail banking. The results presented are part of a wider research of market readiness and AI acceptance, especially in developing economies. The research was conducted in Bosnia and Herzegovina (B&H). The quantitative portion consisted of a survey completed by 671 respondents. This paper focuses on the influence of social factors (perceived humanness, perceived social interactivity, and perceived social presence) on the attitudes towards – and subsequently acceptance of - AI-based services. Chatbots, specifically ChatGPT-4, were the technology the research focused on. The results indicate that perceived humanness and perceived social interactivity have a positive effect on attitudes – and acceptance – of AI-based services. This research could not prove that there is a positive relationship between social presence and attitudes towards AI-based services. The positive relationship between attitude and acceptance was proven as well.

Keywords: *Artificial intelligence (AI), Machine learning (ML), Banking, Technology readiness*

JEL classification*: O32*

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1. Introduction

Artificial intelligence (AI) is a complex term that many have tried to define since it was coined in 1956. There is no widely accepted definition of AI (Allen 1998; Duan, Edwards, and Dwivedi 2019; Kirsh 1991; Monett and Lewis 2018, Nilsson 2009; Winston 1982). For the purposes of this text, the assumed definition is that AI is 'the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity' (Rai, Constantinides, and Sarker 2019, p. 3).

In 2024, AI seems to be ubiquitous – in development, in research, and in daily news articles. The release of ChatGPT in late 2022 led to a major boost of interest and media coverage in all things AI. Leaders from all industries are considering how AI can improve their daily operations and make sure they are keeping up with the fast pace of technology development. AI has major potential to improve operations, from significantly enhancing how repetitive tasks are performed, to lowering costs. Banking is no exception; however, while some perceive banking as an innovative industry (Marous 2017, Cocheo 2020, J.P. Morgan 2021, Citi 2018), others argue it is the exact opposite. During the financial crisis in 2009, Paul Volcker, former US Federal Reserve chief, memorably said that 'the ATM has been the only useful innovation in banking for the past 20 years' (Lumley 2022). King (2014) agrees – nineteenth-century banking principles are still discernible. Whatever the case may be, banking (as any other industry) will have to adapt to the major technological shift in order to remain competitive. Many believe that the combination of humans and technology will be the competitive advantage in banking of the future. Davenport et al. (2019) argue that AI will be more effective if it is used to augment, not replace, humans.

There are many ways in which AI can be used in both back-office and front-office banking operations. While all use cases are relevant research topics, and while it is inarguably important to continue researching the readiness of banks, the focus in this paper is the readiness of customers to accept AI in retail banking.

Readiness for and acceptance/rejection of new technologies has long been an area of research interest among scholars from various fields, including information systems (IS). TAM (Technology Acceptance Model) and different variations of it are some of the most popular research models for assessing technology acceptance. One of the popular expanded versions is The Service Robot Acceptance Model (sRAM), originally developed by Wirtz et al. (2018), that adds 'previously underexplored social and relational variables' as acceptance drivers (Fernandes and Oliveira 2021).

The present study combines TAM and sRAM to assess the readiness of banking customers in Bosnia and Herzegovina for AI-based banking services. The conceptual model presented in this study focuses on the role of social factors in shaping attitudes toward AI-based banking services and intention to adopt AI-based banking services.

1.1. AI in banking

According to Manser Payne, Dahl and Peltier (2021), combining the growth of digital technologies with the concept of servitization (shifting to service-oriented business models, fueled by innovation) results in a new term – digital servitization. It utilizes digital service technologies to create customer value. Despite many being aware that AI and digital servitization in banking offer immense potential, there is not a lot of research on the impact AI has on the value co-creation process. Additionally, Manser Payne, Dahl and Peltier (2021) note that 'organizations employing digital servitization strategies increasingly view AI-enabled technologies as efficient ways to replace human-to-human interactions of frontline service providers or to automate various processes'. As AI becomes more competent at mimicking human cognition and emotions, conversational bots might be considered as actors in the value co-creation process. This calls for research on how client-facing AI is affecting the service exchange, as well as research on consumer acceptance of AI in consumer-facing contexts. The research presented in this paper contributes to this need.

According to Marous (2017), the use of AI is not new in banking. Financial organizations have been using AI to solve issues of different complexity, by simplifying manual processes and making them more accurate, faster, and less costly. AI is now expanding beyond process improvement and is 'becoming the new user interface (UI)'.

Ng (2020) lists AI and deep learning applications in banking, arguing it is now used in everything from deposits and lending, to insurance, payments, investment management, and capital markets. Deep learning can find a way to connect events that appear not to be connected, and is now arguably the best mean for fraud detection, as well as a tool for setting insurance prices and predicting stock market prices. On the other hand, breakthroughs in natural language processing (NLP), along with deep learning, resulted in chatbots that can now do both sales and customer service. Despite further developments, deep learning certainly has constraints (which include anything from implementation issues to ethical issues). The data this technology relies on needs to be unbiased, which is not an easy thing to achieve. The more bias the data – the more bias the algorithm / machine. Specifically for finance, this can easily mean racial and gender discrimination when setting loan rates, interest rates, or insurance premiums. Using AI in large, connected systems (e.g., the stock market) can lead to dramatic consequences (such as another financial crisis, considering the one in 2008 originated from the financial market). Privacy and use of personal data are the main ethical issues to be considered. On top of easily being biased, AI can also easily be unethical. Ng makes an interesting comparison by saying 'AI is the new electricity', but also states that that major opportunity also comes with great responsibility.

De Miranda (2019) explored the impact of AI in finance in a wider sense, by sharing a theory that the acuteness of the 2008 global financial crisis was in part rooted in the fact that non-transparent computer programs started 'a destructive loop that snowballed across the financial system'. This sort of risk is increased by the fact that financial systems are mutually connected and commonly based on similar software. This results in the need for human supervision, which in turn puts ethical and legal limits to using AI in finance. De Miranda concludes that new currencies and new automated transactions may either fortify capitalism or expedite its fall.

King (2018) states that there are two broad areas where AI will affect financial services – interaction/ conversational AI layer between the customer and the institution, and internally within any process a human can learn within a bank that does not heavily depend on social cues. An algorithm will be able to learn as well as a human, and thus might replace them in many aspects. Specifically for retail banking, Boobier (2018) elaborates on the idea that front-office staff might be becoming an endangered species. Banks around the world are already piloting robots in their everyday work. For example, news came out in 2015 that Bank of Tokyo-Mitsubishi UFJ uses a robotic humanoid bank teller (named Nao) in its flagship Tokyo branch. Nao could potentially operate in 19 languages and 'memorize' details about 5.5 million of customers and 100 products. Another example is Pepper, a 1.2 metres tall robot that retails at around $1600 plus software costs. It has a so-called emotion engine, able to recognize human feelings and simulate them. Note that all of this was available prior to launching ChatGPT and other LLM-based agents, which introduced new levels of simulating human behavior and emotion, such as empathy. All of this calls for questioning what the future of retail banking looks like. Bank branches will likely not exist in their current form. Concepts such as café-banks, which offer informal workspaces and combine banking, working, and drinking coffee, are already emerging. It seems to mirror fintech start-ups, that operate through small groups collaboratively working in public spaces. It is not hard to imagine a robot banking advisor in that scenario.

Brown (2020) suggests using AI to boost innovation across the entire product line – from enhancing and simplifying human interfaces using voice and super sensors, to creating new products that manage themselves and combining human talent with collaborative AIs to build new service offerings at new price points.

Karmakar (2020) refers to Bill Gates' famous quote that 'We need banking, but we don't need banks anymore', and expands on that idea by explaining that banks of the future will be built around people and delivered when and where they need it. They will be powered by data and technology. An AI future offers vast amounts of opportunity, but it comes with potential hazards. Navigating the way to a better future will be the ultimate challenge of our time.

When it comes to AI applications in banking, every available study or publication offers its own categorization. For the purposes of this text, AI applications will be divided into operations-focused and customer-focused applications.

Operations-focused applications of AI in banking

There are numerous ways to use AI for any back-office operations in banking. Some of the most prominent use cases are (in no specific order): (1) document analysis, (2) deposits, lending, and crediting, (3) payments, (4) trading, investments, and portfolio management, (5) (cyber) risk management, fraud detection and prevention, and (6) compliance. Since this paper focuses on front-office / retail banking operations, details of these use cases are omitted. Multiple previous publications (such as King 2018) offer a detailed overview of these use cases.

Customer-focused applications of AI in banking

AI could theoretically be used in any segment of client communication, and in any banking operation in general. Prominent use cases for customer-focused applications of AI in banking include (1) wealth management and financial advising, (2) client onboarding, and (2) client relationship management and chatbots. When it comes to financial advising, King (2018) states that fintech startups were the first to introduce robo-advisors. He argues that human advice is now of marginal value; in the vast majority of cases, robo-advisors can do as good of – or better – job than human advisors can. As for client onboarding, using AI for onboarding will mean faster turnaround than when humans perform the service, plus the benefit of having this service available all day, all year, without holidays, weekends, or any types of leave. It will also be able to process more requests with less mistakes.

1.1.1. Client relationship management and the role of chatbots

Chatbots are AI programs that 'simulate conversations with people via voice or messaging' (Xiang 2020), and were chosen for this research as they are amongst the easiest ways to leverage AI to exceed customer expectations. They are becoming the new norm because they can provide 'the immediate and convenient experience that consumers crave' (Tan 2017).

Walch (2019) expands on this by starting that using bots as customer service agents is 'revolutionizing the relationships between companies and their clients'. Chatbots can assist a much larger number of clients, any time of the day, in comparison to human employees. For this reason, AI-enabled chatbots are quickly gaining in popularity as 'the front-line of customer engagement'. Having a contact point at any time can significantly improve time to resolution and customer satisfaction. While chatbots cannot always resolve a query, they can make sure the right people address it. This results in higher productivity since human agents can focus on more complex cases.

Xiang (2020) notes that chatbots can be used for debt collection as well. They are more effective than humans in simple collection scenarios, like informational and reminder phone calls. They can simultaneously speak to how ever many clients, and remain polite and professional regardless of how tense the situation may get.

Boukadakis (2021) states that AI-powered conversational banking gained additional prominence when the COVID-19 global pandemic started and limited person-to-person (banker-to-customer) contact. One of the biggest reasons for increased use of AI-backed voice technology will be its capability to engage clients like never before. These user-friendly tools can save clients the time they would usually spend browsing through menus, looking for detailed information about their savings and spending. Instead, clients could ask questions like 'How much should I budget for eating out, based on my spending on it over the last six months?'. In short, technology makes it possible to maintain meaningful relationships with clients even when they are away from the bank physically.

Levitt (2024) summarized the findings from the fourth annual State of AI in Financial Services Report, produced by NVIDIA, an industry leader in AI computing. Generative AI and Large Language Models (LLMS) are quickly gaining popularity in a wide range of financial services, from marketing and sales to data generation. Customer experience is another popular use case, which means using chatbots, virtual assistants, and recommendation systems to engage new and existing clients.

It is important to keep in mind that every new technology comes with both opportunities and risks. Using chatbots might also mean issues that include but are not limited to data security and financial risks (Vieira and Sehgal 2017, Richad et al. 2019, Alt, Vizeli, and Saplacan (2021).

1.2. Service Robot Acceptance Model (sRAM)

This model was originally developed to examine the consumers' perceptions, beliefs, and behavioral intentions pertaining to the services delivered by robots. This model builds on the initial TAM by adding social-emotional and relational variables as determinants of robot-delivered services. sRAM also draws on the Role Theory (Solomon et al. 1985) and the Stereotype Content Model (SCM) by Fiske, Cuddy and Glick (2007). The Role Theory assumes that functional, social, and cultural norms direct the actions of interacting parties, i.e., service provider/robot and consumers in a particular situation (Fernandes and Oliviera 2021). On the other hand, the SCM sheds light on two main dimensions of interpersonal and inter-group cognition: perceived warmth and competence. While the 'warmth' dimension refers to perceived intentions (friendliness, helpfulness, and sociability), the 'competence' dimension pertains to the perceived capacities (intelligence, skillfulness, and efficiency), as explained by Fiske, Cuddy and Glick (2007). Hence, consumer acceptance will depend on how well robots can meet the functional needs (competence dimension) and the social-emotional and relational needs (warmth dimension) (Fernandes and Oliviera 2021).

Fernandes and Oliveira (2021) also comment on the limitations of sRAM, which they customized for use for a somewhat similar research topic (acceptance of digital voice assistants - DVAs). They note that other frameworks (e.g., the uses and gratifications (U&G) theory) and other drivers such as entertainment (hedonic dimension) or even inhibitors (e.g., privacy concerns and negative attitudes towards robots) can be useful in explaining customer acceptance of DVA and other automated technologies.

2. Research

2.1. Research background and objectives

Social elements of AI-based services entail perceived humanness, perceived social interactivity, and perceived social presence. Perceived humanness refers to the anthropomorphic qualities that the consumer recognizes in robots. Perceived social interactivity refers to the perception that robots display appropriate actions and display 'emotions' according to societal norms (Wirtz et al. 2018). Perceived social presence refers to the extent to which the robot makes individuals feel as though they are in the presence of another social entity (Heerink et al. 2010). Social presence can also be explained as the degree to which users feel that other intelligent beings interact with them within the digital environment (Tan and Liew 2022) or the feeling that another being 'living or synthetic' also exists in the world and appear 'to react to you' (Heeter 1992, p. 265).

The objective of this research is to test the effects of social factors on attitudes towards AI-based services, and therefore acceptance of those services. It aims to provide more insight into banking clients' attitudes towards interacting with non-human entities when contacting their bank. This will mean a significant shift to front-office operations, and understanding how (not) ready the clients are, as well as what the precedents of their acceptance are, is of key importance for banks to make well-informed technology-related decisions.

2.2. Overview of previous research

When it comes to chatbot research in general, a significant number of studies exist; but considering that the technology is on the rise (and has likely progressed faster between late 2022 and mid-2024 than in all the years before), the research will have to switch to a higher gear to be able to keep up. Generally speaking, users expect for chatbots to be high performing, smart, seamless, and personable (Zamora 2017). Svenningsson and Faraon (2019) expand on this and offer guidance on how to develop AI in a way that boosts adoption. Their research shows that a chatbot should (1) avoid small talk and remain formal in communication, (2) let the user know they are speaking to a chatbot and ask how it can assist them, (2) provide specific information in well-formed sentences, (3) ask follow-up questions, and (4) apologize when the context is not understandable, while proceeding to move the conversation forward.

The role of social factors in attitudes and acceptance of AI-based services has been the topic of previous research studies; however, since the sRAM is fairly new, the number of studies that used it is still quite low (for example, Google Scholar search points to 336 papers mentioning sRAM and Wirtz). 'Limited research has acknowledged the role played by social elements on technology adoption since past technologies do not convey the same human-like characteristics' (Fernandes and Oliveira 2021, p. 188). Recent AI advancements have enabled a previously unseen level of social presence for machines, which means the relevance of this type of research has dramatically increased.

Perceived humanness

Ma and Huo (2023) researched the acceptance of chatbots, on the topic of ChatGPT, using the AIDUA (which stands for 'AI Device Use Acceptance') framework, and confirmed that perceived humanness increases consumers' performance expectancy and decreases their effort expectancy about ChatGPT. Gursoy et al. (2011) stated that users who perceive high anthropomorphism in AI devices often think that AI devices with humanlike features threaten their human identity. Referencing this, Zhang et al. (2021) suggest that AI virtual assistants should be designed with a moderate level of perceived humanness. This will help grow trust between users and AI, and minimize the chances of users feeling threatened and fearful due to excessive perception of humanness. Premathilake and Li (2024) researched users' responses to humanoid social robots. They concluded that relationship between perceived humanness and perceived social presence is significant, and that both factors affect users' continued usage intention.

Brendel et al. (2023) wrote an interesting paper on the paradoxical role of humanness in aggression toward conversational agents. They argue that a more humanlike conversational agent is a double-edged sword, as it can both increase and decrease the user's frustration and, consequently, aggression. According to their research, there are three ways in which perceived humanness can impact a user's aggression towards a conversational agent: (1) perceived humanness increases frustration when a conversational agent produces errors; (2) perceived humanness increases service satisfaction, which consequently lowers frustration, and (3) perceived humanness has an effect on the nature of aggression when a user is frustrated (for example, if the conversational agent is less human-like, the user is more likely to use very offensive language).

Perceived social interactivity

Zhang et al. (2021) researched acceptance of AI virtual assistants and confirmed that perceived social interactivity and perceived social presence are positively related to trust. Kim, So and Wirtz (2022) applied social exchange theory to better understand human–robot interactions, and found that perceived social presence and perceived social interactivity have a positive relationship with rapport, consequently driving usage intentions. Aslam et al. (2023) explored drivers of chatbot acceptance, using an extended version of sRAM. They found that, amongst social elements, only perceived social interactivity has an effect on chatbot acceptance.

Perceived social presence

Tan and Liew (2022) researched the effects of m-Commerce chatbot interface on, amongst other things, social presence. They found that social presence from anthropomorphic agents can influence trusting beliefs toward online platforms. Verhagen et al. (2014) focused their research of virtual customer service agents and found that social presence influences the satisfaction that consumers feel about the service encounter. Araujo (2018) researched chatbots; one of the most interesting conclusions found was that there were no major differences in social presence between human-like and machine-like conditions. The author concluded that the interaction style (dialogue) and the medium (messaging interface) might be enough to trigger social presence. McLean and Osei-Frimpong (2019) examined the variables impacting the use of AI voice assistants and confirmed a positive relationship between social presence and usage. Fernandes and Oliveira (2021) also explored the drivers of adoption for digital voice assistants and found social elements to be significant direct drivers of acceptance, primarily through perceived social presence, which is influenced by social interactivity. They could not find a significant effect for perceived humanness. Al-Fraihat, Alzaidi and Joy (2023) researched the adoption of smart voice assistants and found perceived social presence to be one of the necessary predictors for the consumers' intentions to adopt.

2.3. Methodology

A mixed-method research approach was applied, meaning that qualitative and quantitative research was conducted, with the goal of maximizing the benefits and minimizing the shortcomings that both of these approaches come with. The qualitative research is summarized in a previously published paper and consisted of semi-structured interviews with managers from seven banks in Bosnia and Herzegovina (representing the majority of the local bank industry). The research analysis yielded many conclusions, including that Bosnian-Herzegovinian banks agree that their clients still highly value human touch in service encounters (Turnadzic, Pestek and Cinjarevic 2023), especially when it comes to more complex and sensitive topics, such as lending.

For the quantitative part of the research, the data was collected from bank customers in Bosnia and Herzegovina and used to test the proposed conceptual model. The snowball sampling technique was used to collect responses from 671 bank customers. This technique was chosen for its convenience in terms of chain referral (Pasikowski 2023). The survey was anonymous and the respondents were not asked to confirm their current bank. Responses were collected online, primarily using social media (LinkedIn, Facebook) and direct contacts. While web-based surveys are not without their shortcomings, they have a rapid turnaround, high reach, and they make data quality checking easier (Illum, Ivanov, and Liang 2010).

Discarding incomplete responses, the sample consisted of 664 respondents – users of banking services provided by commercial banks operating in Bosnia and Herzegovina. The gender split was fairly even, with women leading at 56%. Most respondents' highest level of education completed is high school (43%), and the majority is employed (66%). The biggest age groups were 36-45 (25%) and 26-35 (22%). In terms of residence (considering there are three entities in Bosnia and Herzegovina), the majority of respondents (81%) lives in Federation of Bosnia and Herzegovina. In terms of household size (including the respondent), the biggest group are those that live in 4-person households (33%). The same percentage (33%) of respondents live in households where the average monthly net income during 2023 was less than 2000 BAM (roughly equivalent to 1000 EURO).

Before accessing survey questions, the respondents were required to watch a video of a conversation with ChatGPT about lending. Lending was chosen as the topic because it is the core of banking. This was mentioned by one of the qualitative research participants, and is a common perception in the industry. International Monetary Fund, Gobat (n.d.) explains that banks do a lot of things, but their primary role revolves around deposits and lending. When answering the questions, respondents were asked to imagine a future where a chatbot run by their bank will be providing information on all services offered by the bank.

All constructs from the research model were measured by scales developed and validated in previous research (see Table 1). Constructs related to social factors are listed in Table 2.

Table 1. Research constructs' references

Model segment	Construct	Measurement scale adapted from previous studies
Social elements	Perceived humanness	Fernandes and Oliveira (2021), Ma and Huo (2023)
	Perceived social interactivity	Fernandes and Oliveira (2021)
	Perceived social presence	Fernandes and Oliveira (2021), Tan and Liew (2022)

2.4. Hypotheses

Four hypotheses were assumed:

H1: Perceived humanness is positively related to attitudes towards AI-based services.

H2: Perceived social interactivity is positively related to attitudes towards AI-based services.

H3: Perceived social presence is positively related to attitudes towards AI-based services.

H4: Attitude towards AI-based services is positively related to acceptance of AI-based services.

2.5. Analysis and discussion of results

Data analysis was conducted through Covariance Based Structural Equation Modeling (CB-SEM), using SmartPLS 4.0 software. Confirmatory Factor Analysis (CFA) was done as the first step. The analysis was also conducted in bootstrapping mode. CB-SEM is usually the path when wanting to confirm theories and their underlying hypotheses; it is theory-driven (Hair et al. 2021, Agic 2018). In line with these guidelines, CFA and CB-SEM were chosen for this research work.

Model goodness-of-fit (RMSEA - Root Mean Square Error of Approximation, TLI - The Tucker and Lewis Index, CFI - Comparative Fit Index, SRMR - Standardized Root Mean Square Residual), outer loadings (see Table 2 for more details), composite reliability (rho_c and Cronbach's alpha), convergent reliability (Average Variance Extracted (AVE)), and discriminant reliability (the Fornell-Larcker criterion and the HTMT criterion) were all checked, as well as basic SEM prerequities (which are (1) normal data distribution, (2) absence of multicollinearity, (3) linearity, (4) homoscedasticity and (5) sample size). See Table 3 for details on RMSEA, TLI (NNFI), CFI, SRMR, and Table 4 for details on Cronbach's alpha, composite reliability, and average variance extracted. Based on all of the above, it was concluded that the used scale and model are a reliable base for the research.

When it comes to sample size, Kline (2016) explains that SEM is, generally speaking, a large-sample technique. However, it is hard to specify what large enough constitutes, at least not in a way that

Figure 1. Research model

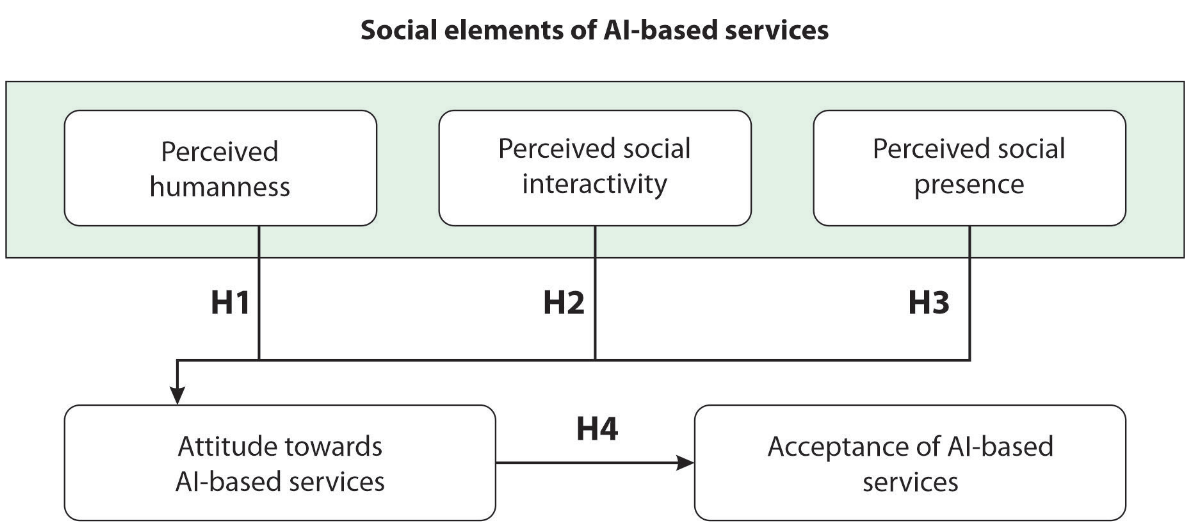


Table 2. Outer loadings

Latent variable	Manifest variable	Codes	ST loadings
Perceived humanness	Banking chatbot's responses feel natural.	PH1	0.849
	Banking chatbot offers a human-like response.	PH2	0.882
	Banking chatbot's responses do not feel machine-like.	PH3	0.615
	Banking chatbot reacts in a very human way.	PH4	0.811
Perceived social interactivity	I consider the banking chatbot a pleasant conversational partner.	PSI1	0.900
	I consider the banking chatbot pleasant to interact with.	PSI2	0.920
	I feel that the banking chatbot understands me.	PSI3	0.745
Perceived social presence	I can feel the human contact with the banking chatbot.	PSP1	0.818
	I can feel a sense of human sociability with the banking chatbot.	PSP2	0.879
	I can feel a sense of human warmth with the banking chatbot.	PSP3	0.871
	I can feel a sense of human sensitivity with the banking chatbot.	PSP4	0.874

Table 3. Model fit indices

Index	**General rule for acceptable fit if data is continuous**	**Value in this research**
RMSEA	< 0.06 to 0.08 with confidence interval	0.063
TLI (NNFI)	≥ 0.95 can be 0 > TLI > 1 for acceptance	0.889
CFI	≥ 0.95 for acceptance	0.899
SRMR	≤ 0.08	0.085

Adapted from: Schreiber et al. (2006)

would be applicable to all cases. The more complex the model (the more parameters there are), the bigger the sample size should be. MacCallum et al. (1999) researched the guidelines for sample size in factor analysis and came to the conclusion most authors agree with nowadays – that there is not a one-size-fits-all approach. Agic (2018) notes that minimal sample size varies between 100 and 500. Wolf et al. (2013) also researched different approaches to determining sample size in SEM models and concluded that more is not always better. They list some of the guidelines provided by other authors (such as a minimum sample size of 100 or 200 (Boomsma 1985), or 5 to 10 observations per parameter (Bentler and Chou 1987)) and describe them as problematic, as they are not model-specific. The '10-times rule' (which says that sample size should be greater than ten times the maximum number of model links pointing towards latent variables in the model) has been popular (Kock and Hadaya 2016; Hair et al. 2011; Jayaram et al. 2004), but that does not mean it cannot lead to inaccurate estimates (Kock and Hadaya, 2016; Goodhue et al. 2012). While the validity of the '10-times rule' is questionable, the sample size in this thesis exceeds it, thus conforming to widely accepted standards.

It does not make sense to include every index included in the program's output. However, it is also important to avoid choose those fit indices that indicate the best fit (Hooper et al. 2007). Different authors suggest including different indices. Kline (2016) recommends including model chi-square statistic, RMSEA, CFI, and the SRMR. Schreiber et al. (2006) recommend TLI, CFI, and RMSEA for one-time analyses (which is the case in this research).

The main source for the strict cutoff criteria are Hu and Bentler (1999). They say that CFI and TLI values should be 'close to .95 or greater'. Brown (2015) explains that the 'use of the phrase 'close to' is not accidental, because the recommended cutoff values were found to fluctuate as a function of modeling conditions and whether or not an index was used in combination with other fit indices.

When discussing TLI, Schermelleh-Engel explain that more complex models are penalized by a downward adjustment, while more restrictive models are rewarded by an increase in the fit index.

Ringle et al. (2024) note both 0.08 and 0.10 as acceptable thresholds for SRMR.

Marsh et al. (2004) wrote a paper on the dangers in overgeneralizing Hu and Bentler's findings. Despite Hu and Bentler suggesting caution, many reseachers 'have inappropriately promoted their new, more stringent guidelines for acceptable levels of fit into something approaching the golden rules' (p. 322). The results by Hu and Bentler have limited generalizability in typical practice. While it might be disappointing to researchers wanting clear rules, 'interpretations of the degree of misspecification should ultimately have to be evaluated in relation to substantive and theoretical issues that are likely to be idiosyncratic to a particular study' (p. 340).

Since RMSEA fits the criteria, SRMS fits the less strict criteria, and CFI and TLI are close to less strict cutoffs (0.90), after thoroughly reviewing both theory and other versions of the model, the author found the model formed for this research to be a good fit. Its complexity makes it hard for all metrics to fit more strict acceptable ranges. While this paper only presents the parts of the model related to social elements, the full model also included functional elements (perceived ease of use, perceived usefulness, and perceived social norms) and technology readiness elements (innovativeness, optimism, discomfort, and insecurity).

It is also worth noting that R-Square, the coefficient of determination (which Hair et al. (2021) define as 'the variance explained in each of the endogenous constructs and a measure of the model's explanatory power') is satisfactory (above 0.64 for acceptance; above 0.81 for attitudes).

Table 4. Composite and convergent validity

Latent variable	Cronbach's alpha (standardized)	Composite reliability (rho_c)	Average variance extracted (AVE)
Humanness	0.866	0.872	0.634
Interactivity	0.886	0.891	0.737
Social presence	0.918	0.919	0.741

Table 5. Hypotheses' direct effects

Hypothesis		Beta	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	
H1	PH -> ATT	0.145	0.144	0.054	2.706	0.007	Confirmed
H2	PSI -> ATT	0.157	0.159	0.046	3.389	0.001	Confirmed
H3	PSP -> ATT	-0.084	-0.085	0.046	1.818	0.069	Not confirmed
H4	ATT -> CA	0.778	0.778	0.021	37.044	0.000	Confirmed

Table 6. Hypotheses' specific indirect effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
PH -> ATT -> CA	0.113	0.112	0.042	2.687	0.007
PSI -> ATT -> CA	0.122	0.123	0.036	3.395	0.001
PSP -> ATT -> CA	-0.065	-0.066	0.036	1.814	0.070

There is also partial (indirect) mediation to consider. According to Ryu and Cheong (2017), the mediation effect can be specified as an indirect effect (Alwin and Hauser 1975; Bollen 1987) such as 'the indirect effect of an independent variable (X) on a dependent variable (Y) via a mediator (M)' in which X affects M, which in turn affects Y. The results in the table above are in line with direct effects shown in the previous table.

Beta should be positive if the assumed relationship is positive, and vice versa. As for P values (a measure for null hypothesis significance testing), the number shows how likely it is that the data would have occurred by random chance (i.e., that the null hypothesis is true). Acceptable ranges vary depending on the author. Hair et al. (2022) use <0.05 as the norm and are amongst the most cited; however, many use more stringent approaches such as <0.01. Zhu (2016) is just one of the authors questioning the trend of aiming for lower P values and claiming statistical significance as a result.

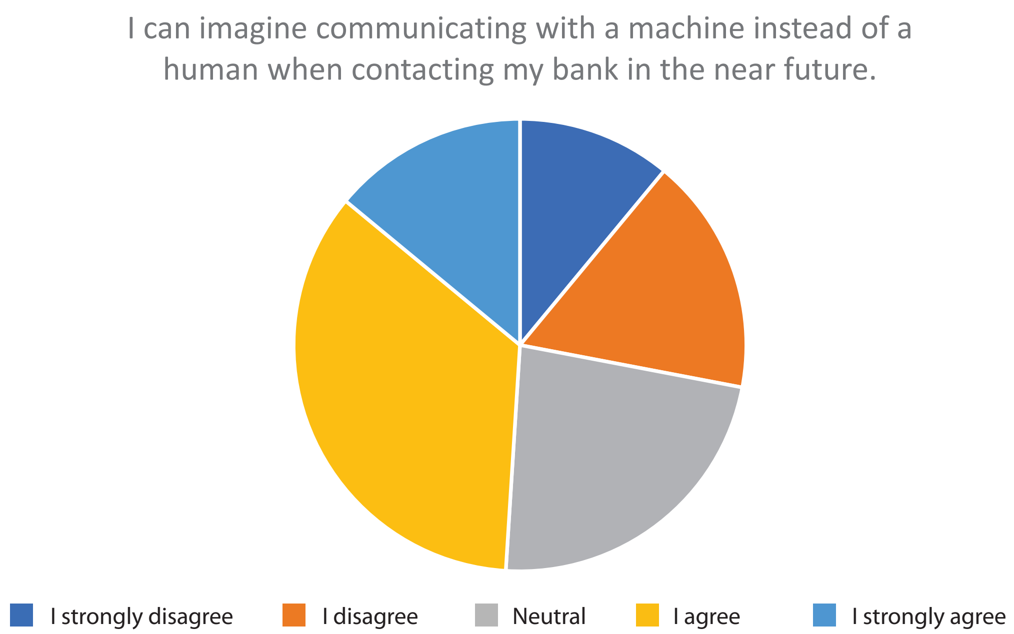
Before diving into model testing and hypotheses, with the goal of better understanding the effects of social factors on attitudes and acceptance of AI, it is important to consider how open users are (not) to communicating with AI. Almost half of the survey respondents can imagine communicating with a machine instead of a human when contacting their bank in the near future, which is a good start (see Table 7 and Figure 2 below).

Considering betas and P values (see Tables 5 and 6), the first, second and fourth hypotheses in this group were proven. The third hypothesis could not be proven.

Table 7. Openness to non-human communication

I can imagine communicating with a machine instead of a human when contacting my bank in the near future.	Percentage
I strongly disagree	11%
I disagree	17%
Neutral	23%
I agree	35%
I strongly agree	14%

Figure 2. Openness to non-human communication



3. Conclusion

Perceived humanness (meaning, the anthropomorphic qualities that humans perceive in AI entities) and perceived social interactivity (meaning, the perception that AI entities display 'emotions' in line with societal norms) have a positive effect on attitudes – and acceptance – of AI-based services. However, this research could not prove that there is a positive relationship between social presence and attitudes towards AI-based services. Fernandes and Oliveira (2021), whose work served as basis for parts of the research model used for this thesis, researched the drivers of adoption of digital voice assistants, and concluded that the impact of social elements was only marginally significant. Interestingly, Zulfakar et al. (2022) researched customer acceptance and intention to use service robots in the hospitality industry, using sRAM, and found that none of the three social-emotional elements are essential in determining acceptance. They interpreted their research results as indicating that customer acceptance is much more related to functionality than it is to the machine's perceived social behavior. This is closely related to the research of Wang et al. (2023), that focused on user adoption of healthcare chatbots. While the authors found perceived social presence to be of key significance, the social features of chatbots are only useful (meaning, they have a positive effect on trust and satisfaction) when combined with functionality.

The attitude – intention relationship in the context of AI-based services was proven. Attitude, as expected, is positively related to acceptance. As per Dickinger et al. (2008, p. 6, 7), 'attitude is directly related to behavioural intention because people will only have intention to perform behaviours towards the things for which they have positive feelings'. Zhu et al. (2012) and Wong et al. (2013) are some of the many authors that showed that attitude positively correlated with user intention of use. In the realm of AI research, Rafiq et al. (2022) explored the intention to adopt AI chatbots in tourism, and found that the consumers' affective and cognitive attitudes were significant predictors of AI-chatbot adoption.

3.1. Research implications

From a theoretical standpoint, this paper seeks to expand the limited body of knowledge on the influence of social factors on AI acceptance. The value of researching social factors in AI acceptance is directly related to how advanced AI technology is (meaning, how well it can portray social behavior). AI consumer technology, specifically chatbots, have seen radical improvements over the past two years, making this research topic much more relevant. As time goes by and this technology continues to develop, the research topic will grow even more important. Since ChatGPT was first released in November 2021, several new and improved versions of the most popular chatbot were released (at the moment of writing this article, ChatGPT-5 is pending, and an improved version of ChatGPT-4 was released in May 2024). Every version of the chatbot came with significant improvements in the accuracy of outputs and the natural feel of the conversations. Given this major progress, any and all research concerning chatbots (from how best to develop them to what the users need to adopt the new technology as a main form of communication) is much needed.

From a managerial standpoint, the results of this study identify some of the drivers of AI-based services adoption among bank customers and thus allow bank managers to design AI-based services that will align with the expectations and needs of bank customers. This particular study is especially interesting for transitional economies. In the case of Bosnia and Herzegovina, the present study showed that the vast majority of local banks can be classified as digital laggards. The overall research conclusion is that Bosnian-Herzegovinian banks know little about the potential use cases of AI in banking and do not have developed strategies as to how to implement it going forward. Using academic and commercial research can hopefully assist banks on their way to implementing AI, and then fully exploring its benefits. One of the major prerequisites of doing so is understanding the stance of customers, starting with the drivers of their future adoption of AI-based services.

While banking was chosen as the industry of focus for this research (due to the fact that a big portion of the planet will at some point be a bank's client), research findings related to AI acceptance are relevant for other industries as well. This is especially true for industries that deal with sensitive data (as banking does with financial information and money), such as insurance and healthcare. As one of the respondents in the related qualitative research (Turnadzic, Pestek and Cinjarevic 2023), put it, openness to using AI depends on the service type (e.g., it is easier to talk to AI about withdrawing money than about taking out a housing loan).

3.2. Research limitations and further research recommendations

Every technology acceptance model has its own inherent limitations. The research model used (see Figure 1) in this thesis inevitably inherits some of those limitations. The same goes for the analysis – SEM, as well as SmartPLS, have both major benefits and some limitations. Conducting the research using other techniques and software would be beneficial. The research model could also be simplified for future similar studies.

The effects of sample size are a never-ending topic amongst researchers. While the sample size in this thesis was satisfactory, the author's recommendation is to expand the research in terms of sample size, as well as to explore the effects of different demographic characteristics. Additionally, as the majority of respondents were based in Federation of Bosnia and Herzegovina, it would be worthwhile increasing the number of respondents from Republika Srpska and District Brcko. Outside of the country, it would be interesting to see how the results from other transitional economies (those post-war like Bosnia and Herzegovina and others) would compare to this study. Expanding on that, it would be useful to conduct the research in developed economies and see if/how the results differ.

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